Different factors for different causes: Analysis of the spatial aggregations of fire ignitions in Catalonia (Spain)

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Abstract

The present study analyzes the effects of different socioeconomic factors on the frequency of fire ignition occurrence according to their etiology. The spatial aggregation patterns of fire ignitions in the region of Catalonia was assessed independently for each specific ignition cause, and the point-based data on ignitions was interpolated into municipality-level information, using kernel methods as the basis for defining five ignition density levels. Afterwards, the combination of socio-economic factors influencing the ignition density levels of the municipalities of Catalonia was analyzed for each ignition cause using a Principal Component Analysis. The obtained results confirmed the idea that both the spatial aggregation patterns of fire ignitions and the factors defining their occurrence were specific for each of ignition cause. For example, intentional fires and those of unknown origin were found to have similar spatial aggregation patterns, the presence of high ignition density areas being related to high population and high unemployment rates. Additionally, it was found that fires originated from forest work, agricultural activities, pasture burning and lightings had a very specific behavior on its own, differing from the similarities found on the spatial aggregation of ignitions originated from smokers, electric lines, machinery, campfires and those of intentional or unknown origin. The study provides the basis for rejecting the traditional approach of dividing the ignitions merely into natural or human-caused before analyzing the factors influencing their aggregation patterns.

Introduction

Fire ignitions display specific spatial and temporal aggregation patterns depending on their causes [1, 2, 3, 4]. They usually match the spatial distributions of the environmental and socioeconomic factors that can induce their occurrence. Accordingly, assessing the risk of fire ignition occurrence and identifying the possible factors driving their patterns of aggregation are key issues for adequate design and implementation of fire prevention measures [5, 6, 7]. However, many previous studies aiming at identifying socioeconomic or environmental factors related to the occurrence of human-associated ignitions have not explicitly taken into account their specific etiology (intentional, accidental, due to negligence, etc.), probably owing to the difficulties met in gathering this type of information.

Not segregating ignitions according to their specific etiology can result in combining events that often have different spatial and temporal occurrence patterns [2, 3, 4, 8]. We can assume that independently analyzing the aggregation patterns of fire ignitions according to their cause would improve the recognition of their specific occurrence patterns, and also enhance the chances of identifying related factors underlying the recurrence of fire ignitions [6]. Thus the knowledge obtained can provide a better framework for designing cause-specific fire prevention measures to reduce the number of ignitions and protect valuable resources [4, 8, 9].

The variation in the frequency of human-caused ignitions can be analyzed at different spatial scales. For example, regular grids can be used to display the occurrence or frequency of fire ignitions at this scale, and compare these with potential influencing factors [5, 10, 11, 12, 13, 14]. Other studies have analyzed the effect of aggregated factors on the number of ignitions occurring inside administrative limits, such as municipalities or counties [15, 16, 17, 18]. In this case, the study of the aggregation pattern of fire ignitions allows the characterization of events related to proxies or predictors based on socioeconomic indicators from historical census. This type of analysis implies loss of information about fine-scale variations on the spatial occurrence of ignitions, and potential errors due to spatial inaccuracies in recording the ignition points [19]. However, it substantially enhances the modeling potential of the analysis.

To bridge these two approaches, *kernel*-based methods have recently been used to convert point-based data into continuous information about fire occurrence densities [1, 4, 7, 19].

These methods can generate ignition density information for a given administrative scale, which can then be used for future analyses of influencing factors.

In the present study we set out to analyze the effects of different socioeconomic factors on the frequency of fire ignition occurrence. For this purpose, the spatial aggregation patterns of fire ignitions in the region of Catalonia were analyzed independently for each specific ignition cause. The spatial analysis of the segregated ignitions was then used as a basis to interpolate the point-based data on ignitions into municipality-level information highlighting differences in both the aggregating pattern of ignitions and the factors determining them.

2. Material and Methods

Ethics Statement

The data on ignition records and fire causes, used on the study, was provided by the Government of Catalonia (www.gencat.cat). Permit for using the data was given under the condition of using it strictly for scientific purposes, any reporting being confined to final analysis or results. No other ethic conflict was identified for the study.

2.1. Catalonia and its recent fire ignition history

The area of study encloses the whole region of Catalonia, in the north-east of Spain, covering 32 000 km^2. The region is recurrently affected by forest fires, with some severe years, like1994, in which 1217 fires affected more than 76 500 ha, prompting the government to make additional efforts to record the locations of the fire ignitions and to investigate their causality. After 1994 and during the studied period 1995–2008, a total of 9534 fires larger than 100 m^2 were recorded (Table 1).

Table 1.

Catalonia is one of the most populated regions of Spain, with over 7 million inhabitants. The demographic distribution is not homogeneous. It is clustered in some areas, usually near the coast (e.g. the city of Barcelona), and leaves large underpopulated areas. The region is divided into 946 municipalities (Figure 1), also highly heterogeneous in size and socio-economic characteristics. This socioeconomic variability is expected to influence the aggregation patterns of the ignitions.

Figure 1.

2.2 Ignition density estimation using kernel methods

Kernel methods were applied to estimate variation in the density of fire ignitions. The kernel method is a non-parametric technique that uses the allocation of the fire ignitions as input to generate a continuous estimation of the accumulated density, based on probability density functions [20, 21]. Mathematically, the kernel density function for n observations can be defined as:

$$\hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K\left(u_i\right), \quad \text{Eq. 1}$$

for $u_i = (x - X_i) / h$, where K is the kernel function, h is the bandwidth or smoothing factor, and x_i is the value of the observed variables. In the case of point events like ignitions, X_i corresponds to the vector of coordinates of the ignition, and therefore the difference $(x - X_i)$ refers to the distance between a point where the density function is to be estimated and each of the observed events used to define the density. In the present study, we used the spatial statistic package *SPlancs* [22] adapted for R [23] to estimate the probability densities. A quartic kernel function with a fixed bandwidth was applied, as a method for correcting the border effect [24, 25].

A characteristic of the kernel methods is their flexibility, and the final result depends more on selecting an adequate magnitude for the radius of search or bandwidth h than on the selection of the kernel function (normal, triangular, gaussian, or quartic), or on the method for selecting the radius of search (fixed or adaptive) [26, 27]. Therefore, the selection of the bandwidth took into account both the size of the municipalities and the spatial distribution of the ignitions, following the objectives of the study. First, we compared the theoretical radius of the mean sized municipality (4119.4 m) with the mean random distance (RD_{mean}) between ignitions per municipality, multiplied by two (following [19, 28]).

A preparatory analysis of the spatial distribution of the fire ignitions was also implemented in order to identify spatially aggregated ignition causes. The spatial aggregation analysis calculated the observed mean distance between ignitions (OMD), the expected mean distance for the total area of study (EMD), the nearest neighbor ratio (NNR = OMD/EMD), and the ZScore, indicating how much NNR deviated from a fully random distribution of the ignitions (Table 2).

Table 2.

The preparatory analysis indicated that all the ignitions, per cause, were spatially aggregated. The RD_{mean} value was found to vary substantially according to the ignition cause, and so was used to define the *h* or bandwidth for the kernel density function for each set of ignitions. Hence to study the intentional (*int*) ignitions, a bandwidth of 4000 m was applied, 5000 m for those whose origin was agriculture (*agr*), 6000 m for those whose cause was lightning or unknown (*lig*, *unk*), 7000 m for ignitions caused by smokers (*smo*), and 8000 m for ignitions caused by campfires, pasture burning, forest work or electric lines (*cam, pas, for, ele*).

2.4 Converting fire densities into municipal level risk indices

Modeling the effect of socio-economic factors on the risk of occurrence of fire ignitions at municipal level requires harmonizing and scaling the data [28]. This harmonizing process includes converting the ignition probability densities into a single value for each of the municipalities. For this purpose, we generated a square grid of points 500 by 500 m, where the probability densities of the ignitions were estimated for each of the ignition causes separately, for the period 1995–2008. The average value of the points within each municipality was then calculated. Finally, one of five ignition density classes was assigned to each municipality (range levels: very low, low, medium, high, and very high).

We selected a number of potential predictors of ignition density variation among municipalities (Table 3): area of the municipality (*Area,* km^2), mean elevation of the municipality, in meters above sea level (*Ele, m a.s.l.*) population density in 2001 (*Pop2001, inhabitants per* km^2), change in population between 1998 and 2008 (*PopVar98_08, percentage*), unemployment (*Unemploy, percentage versus total population*), unemployment of active population (*Unemploy16_65, percentage versus population ages 16 to 65*), vehicle density in 2002 (*VehicDens,* vehicles registered per 1000 inhabitants), house density in 2001 (*HouseDens, houses per* km^2), household capacity in 2001 (*Household, houses per inhabitant)*, delinquence in 2001 (*Conflict, registered felonies per house*), rural relevance in 1999 (*PRural, percentage of rural land*), agricultural relevance in 1999 (*PAgr, percentage of labored land*), forestry relevance in 2001 (*PFor, percentage of forest land)*, pasture utilization in 2000 (*PPast, percentage of pasture land*), cattle presence (*CattleDens*, bovine and equine cattle head per km^2 in 1999), agricultural mechanization in 1999 (*AgrMachines*, number of tractors, harvesters, etc. per km^2 in 1999), camping presence in 2002 (*CampDens,* number of campsites per km^2),and hotel presence in 2002 (*HotelDens,* number of hotels per km^2).

Some of the variables were retrieved from databases of national and regional institutes such as the Spanish National Institute for Statistics (INE) and the Statistics Institute of Catalonia (Idescat). The variables concerning population and agriculture were based on the *Censo de Población y Viviendas de 2001*, the *Censo Agrario de 1999* and the *Censo Agrario de 2009*. These censuses provided information about the state and change of different socio-economic variables at municipal level during the study period.

Table 3.

The portfolio of socio-economic variables was first analyzed using correlation matrices and principal component analysis (PCA), in order to identify noteworthy correlations or confounding effects between the variables considered. In some cases, the variables were transformed using the natural logarithms in order to reduce the effects of outliers, and to reduce strong deviations from normality. More complex transformations were avoided in order to retain the original variables as much as possible. Finally, the main axes resulting from the PCA, and the highest ignition levels, were combined to form the results.

3. Results

3.1. Spatial aggregation patterns

The spatial distribution of ignition densities at municipal level showed clearly different patterns, depending on the cause of the ignition (Figure 2 and Figure 3). For example, densities of ignitions caused intentionally (*int*), those whose cause was not identified (*unk*) or those originating from campfires (*cam*) followed similar spatial patterns. In this case, municipalities close to the coast, or surrounding Barcelona were more likely to present high levels of ignition densities. The ignitions whose origin was smokers (*smo*), machinery (*mac*), or electric lines (*ele*) were found to be located near main transportation routes, whereas ignitions related to agriculture (*agr*) and lightning (*lig*), were aggregated in the central area of the region, although they showed a lesser degree of similarity than those previously stated. Finally, ignitions caused by pastures (*pas*), and forest management operations (*for*) presented a distinct spatial pattern. In the case of burning pastures, most ignitions tended to be in the north-east of the region, whereas ignitions due to forest work (*for*) were mainly in the north-west.

Other spatial features could be observed from the results, such as a clear gradient of ignition density levels, especially in the case of less common ignitions, for which the use of larger bandwidths was needed to define the ignition probability densities.

Figure 2.

Figure 3.

3.2 Socio-economic predictors

For the portfolio of socio-economic variables, the PCA identified six different axes, using the criteria of Eigen values higher than 1 (Table 4). After the data was rotated for a clearer analysis, the axes were named according to the variables that received the highest scores, thus: "*population*", "*agriculture*", "*unemployment*", "*recreation*", "*cattle*" and "*cars*". These six axes explained 74.25% of the total variance.

Table 4.

As described in the methodology, the main axes resulting from the PCA were used to define the combination of factors that might explain the classification of a municipality in a specific ignition level. Crossing the PCA axes by ignition causes resulted in a large number of combinations. Therefore, only the four most common ignition causes were considered for thorough analysis, and the representation of the results included only selected axes.

The pattern of the ignition levels associated with unknown (*unk*) causes was very similar to the intentional (*int*) one (Figure 4). The highest ignitions levels were mostly differentiated according to high values of population and settlement-related variables, and to a lesser degree by the presence of forest areas and high unemployment rates.

Figure 4.

In the case of causes related to agriculture (*agr*), the ignition levels were mainly differentiated according to the presence of agricultural land and agricultural machinery, the highest ignition levels being where the agrarian activity was most intense. By contrast, the population patterns did not seem to have an important role in classifying the ignition levels (Figure 5). An interesting though expected result was that causes related to lightning (*lig*) usually occurred in untilled areas (i.e. forested ones), with no relation to population patterns or unemployment rates.

Figure 5.

When all the ignition causes were plotted together against the PCA axis, it was observed that depending on the cause, the very high ignition levels were located in very different areas (Figure 6). This meant that the combination of socio-economic factors used to explain the aggregation of the ignitions on the municipality level was driven by the specific ignition causes for the very high ignition levels. Some clusters were nevertheless observed between causes, one formed by agriculture (*agr*), pastures (*pas*) and lightning (*lig*), a second one formed by the presence of forest work (*for*) and machinery (*mac*), and a third and larger one formed by unknown (*unk*), intentional (*int*), smokers *(smo)*, campfires (*cam*),and electric lines (*ele*).

Figure 6.

4. Discussion

The present study analyzes the spatial aggregation patterns of fire ignitions in Catalonia during the period 1995–2008. For this purpose, the data on fire ignitions were segregated according to their specific ignition cause. As expected, the aggregation patterns of the ignitions varied depending on the ignition etiology [2, 3, 4].

The methodology used to convert the ignition densities into a municipal level scale entails a significant loss of spatial variation for the ignition density. For example, it has been demonstrated that factors related to the proximity of infrastructures influence the occurrence of ignitions at smaller scales than administrative borders [14]. However, the proposed homogenization at administrative levels (municipality) is required to develop a regional level fire management strategy [28]. It allows the analysis of the role of different socio-economic factors influencing the density of ignition level, as the data collected for those factors are usually reported at municipal level.

The divergences on the allocation of ignition densities according to their cause emphasizes the need to consider each ignition group as independent, in particular when the factors related to its occurrence are to be assessed. The different location of *risky areas* identified in the spatial analysis provided a basis for rejecting the traditional approach of dividing the ignitions merely into natural or human-caused before analyzing the factors influencing their aggregation pattern. As expected, the spatial variation found on such patterns was linked to a combination of socioeconomic factors, which act as surrogates of the many variables directly related to the occurrence of ignitions. For example, intentional fires and those of unknown origin not only had similar spatial aggregation patterns, but in both cases variables related to "*population"* concentration and "*unemployment"* (in the PCA axes) had a strong influence on such aggregation. These results agree with those of Prestemon and Butry [2], who found intentional fires in Florida to be more common in highly populated counties with higher rates of unemployment. The strong parallelism between intentional and unknown causes suggests that several fires of unknown origin may in fact be caused by arsonists.

For most of the ignition causes, the influence of the axis "*population*" determines the occurrence of very high levels of ignition densities (Figure 5). The main variables defining an increase in the value of the "*population*" axis are: housing and population densities, presence of conflicts, hostelling capacity and population growth. Therefore, the influence of this axis on the identified risk areas agrees with what has been reported in several studies focused on the analysis of the main factors influencing human-caused ignitions [11, 16, 18, 29]. The tendency of a large number of ignition causes to aggregate similarly, such as the ones reported above, suggests that they are triggered by similar socio-economic factors. However, other ignitions (e.g. caused by rural activities) show a divergence in both the aggregation patterns and the influence of factors underlying their aggregation. Therefore, their detection and subsequent analysis is often hidden by the more common ignition causes or the larger set of causes presenting a similar aggregation pattern.

The observed variations among ignition causes in terms of location of risk areas, and socioeconomic factors related to the spatial distribution of ignition clusters, underline the need (i) to implement these analyses separately for each ignition cause and (ii) to consider the specific ignition regime and socio-economic reality of the area or region of study [30] when defining fire risk prevention strategies. Additionally, the aggregations of fire ignitions not only differ spatially, but often temporally, according to their causes. For example, a preliminary analysis of the seasonality of the ignition occurrence shows that in Catalonia the ignitions of intentional cause, or due to lightning, smokers, electric lines, engines, campfires, and most of the unknown ones, tend to occur during the summer, whereas ignitions caused by rural work such as those linked to agriculture, forest work and pasture burning, tend to occur between January and April.

It can be assumed that a deeper knowledge of the location and timing of fire ignition occurrence, per ignition cause, must translate into more cost-efficient prevention measures that must be oriented to limit the factors favoring ignition occurrence. Such improvement will be based on implementing specific preventive measures depending on the ignition cause, from improving awareness and education in the case of smokers or recreational activities, regulation and practice control in the case of rural work, and law enforcement and vigilance in the case of intentional fires, with specific emphasis on the location of such measures. The usefulness of the findings for implementing prevention strategies could be further improved if linked with additional research on the conditions that cause an ignition to become a socially damaging fire.

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TABLES

Table 1. Number of ignitions recorded by cause in Catalonia for the period 1995–2008.

Cause	Number	%
Intentional	2354	24.69
Agriculture-related	1398	14.66
Unknown	1087	11.40
Lightning	1025	10.75
Smokers	595	6.24
Electric lines	505	5.29
Forest work	356	3.73
Machinery	314	3.29
Campfires	262	2.75
Pasture burning	188	1.98
Others	1451	15.22

Table 2. Spatial aggregation analysis of the ignitions, according to their cause. OMD: mean observed distance between ignitions, EMD: expected mean distance for the total area of study, NNR: nearest neighbor ratio, ZS: Z Score

Cause	2 × RDmean	EMD	OMD	NNR	ZS
Intentional (*int*)	3693.1	2441.6	892.9	0.37	-58.87
Agriculture (*agr*)	4756.6	3158.5	1762. 6	0.55	-31.61
Unknown (*unk*)	5554.6	3602.3	1891.1	0.52	-29.96
Lightning (*lig*)	5554.6	3653.7	2231.9	0.61	-23.83
Smokers (*smo*)	7345.5	4683.5	2631.6	0.56	-20.44
Electric lines (*ele*)	7973.4	5034.8	3035.2	0.60	-17.07
Forest work (*for*)	9496.6	3329.2	3751.9	1.13	4.58
Machinery (*mac*)	10111.8	5987.7	4064.9	0.68	-10.89
Camp fires (*cam*)	11069.8	6921.3	4054.4	0.59	-12.83
Pastures (*pas*)	13068.1	7588.5	3509.9	0.46	-14.10

Table 3. Socio-economic variables included in the analysis.

Variable	Mean	Standard deviation
Area	30.8	34.9
Ele	461.7	413.6
Pop2001	373.0	1455.5
PopVar98_08	17.5	19.1
Unemploy	0.02	0.01
Unemploy16_65	0.03	0.02
VehicDens	937.4	2665.1
HouseDens	106.5	418.5
Household	0.28	0.02
Conflict	0.08	0.09
PRural	0.64	0.27
PAgr	0.30	0.26
PFor	0.20	0.20
PPast	0.06	0.14
CattleDens	16.1	26.6
AgrMachines	4.1	3.9
CampDens	0.02	0.07
HotelDens	0.12	0.47

Table 4. Results of the principal component analysis applied to the variables considered for analyses. Values correspond to the *varimax* rotation. In parenthesis the percentage of the variance explained by each axis.

	Axis 1 **"population"**	**Axis 2** **"agriculture"**	**Axis 3** **"unemployment"**	**Axis 4** **"recreation"**	**Axis 5** **"cattle"**	**Axis 6** **"cars"**
	(29.6%)	*(15.5%)*	*(9.5%)*	*(7.6%)*	*(6.4%)*	*(5.6%)*
LN(Area)	-0.361	-0.466	0.028	0.061	0.151	-0.094
LN(Ele)	-0.519	-0.637	-0.153	-0.026	0.100	-0.178
LN(Pop2001)	**0.876**	0.289	0.147	0.099	0.034	-0.125
PpopVar98_08	0.478	-0.007	0.073	0.160	0.028	0.554
Unemploy	0.177	0.014	**0.979**	0.057	-0.019	0.004
Unemploy16_6	0.112	0.023	**0.990**	0.039	-0.018	-0.017
LN(HouseDen	**0.883**	0.289	0.150	0.077	0.042	-0.127
LN(Household)	0.522	0.092	0.145	-0.525	0.232	-0.083
LN(VehicDens)	-0.252	0.012	-0.053	-0.058	0.071	**0.826**
LN(Conflict)	0.698	0.035	0.058	0.140	-0.110	0.011
PRural	-0.702	-0.027	-0.122	-0.069	0.494	-0.099
PAgr	-0.244	**0.833**	-0.059	-0.230	0.263	-0.048
PFor	-0.238	-0.772	-0.017	-0.098	0.118	0.109
PPast	-0.336	-0.455	-0.090	0.395	0.319	-0.189
CattleDens	-0.028	0.079	-0.004	0.012	**0.867**	0.109
AgrMachines	0.089	**0.872**	0.021	-0.046	0.192	-0.001
CampDens	0.182	-0.049	0.118	**0.785**	0.038	0.072
HotelDens	0.536	-0.027	0.060	**0.665**	0.009	-0.122

Figure Legends

Figure 1. Location of Catalonia (left), and boundaries of the municipalities (right), including the administrative provincial capitals.

Figure 2. Levels of ignition density by municipality, for fires intentionally originated, due to agriculture labor, of unknown origin, or caused by lightnings, smokers or electric lines.

Figure 3. Levels of ignition density by municipality, for fires caused by forest work, machinery, campfires or pasture burning.

Figure 4. Average values for the causes intentional (*int*) and unknown (*unk*) for the three main axes of the PCA. (Axis 1 = "population", Axis 2 = "agriculture" and Axis 3 = "unemployment"). Numbers represent the ignition levels (1 = very low, 2 = low, 3 = medium, 4 = high and 5 = very high). Lines represent twice the standard error of the means represented

Figure 5. Average values for the causes related to agriculture (*agr*) and lightning (*lig*) for the three main axis of the PCA.. Numbers represent the ignition levels. Lines represent twice the standard error of the means represented.

Figure 6. Average values for the highest ignition level (5 = very high) according to the causes and selected PCA axis. Lines represent twice the standard error of the means represented.

Figure
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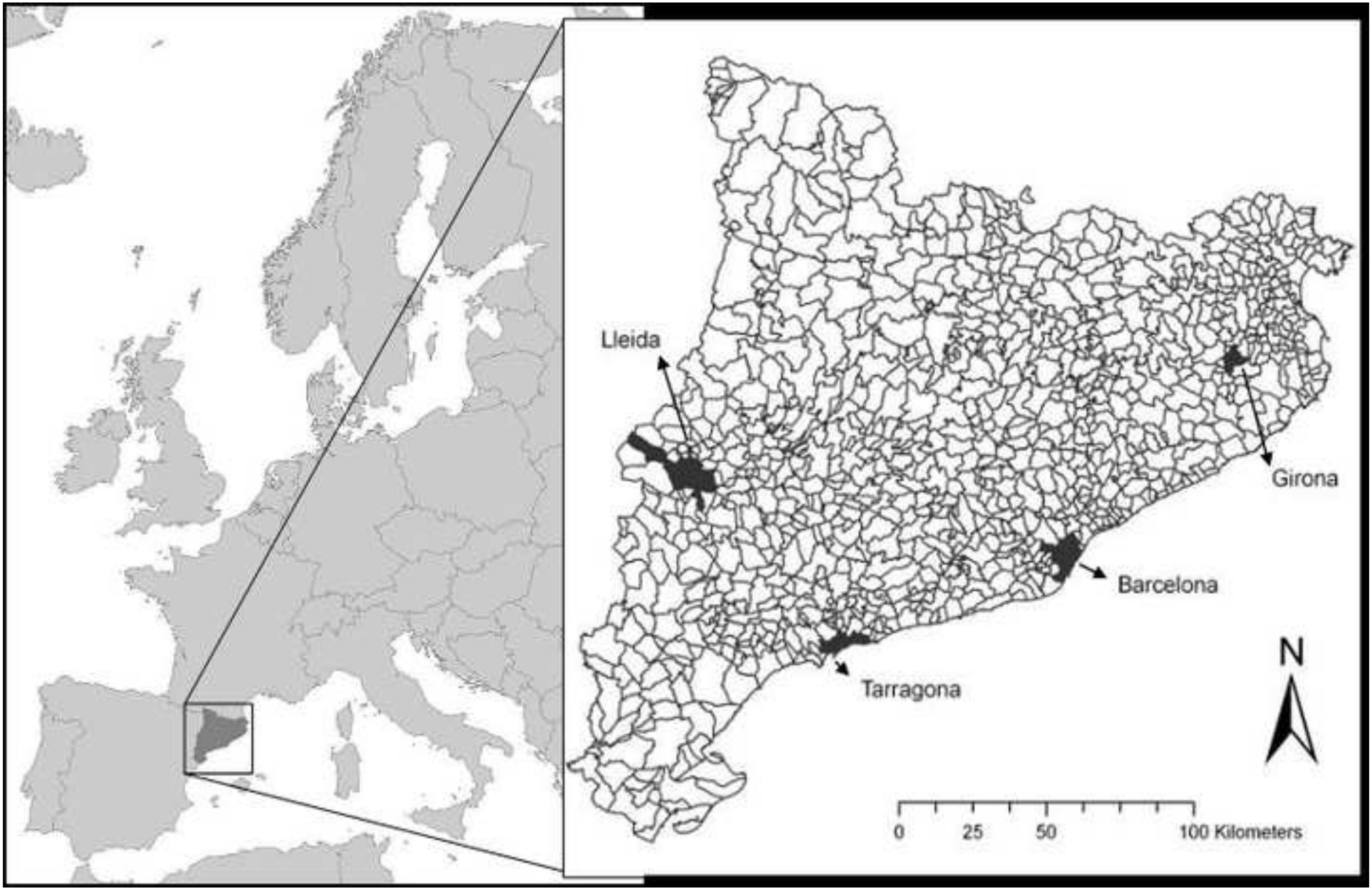

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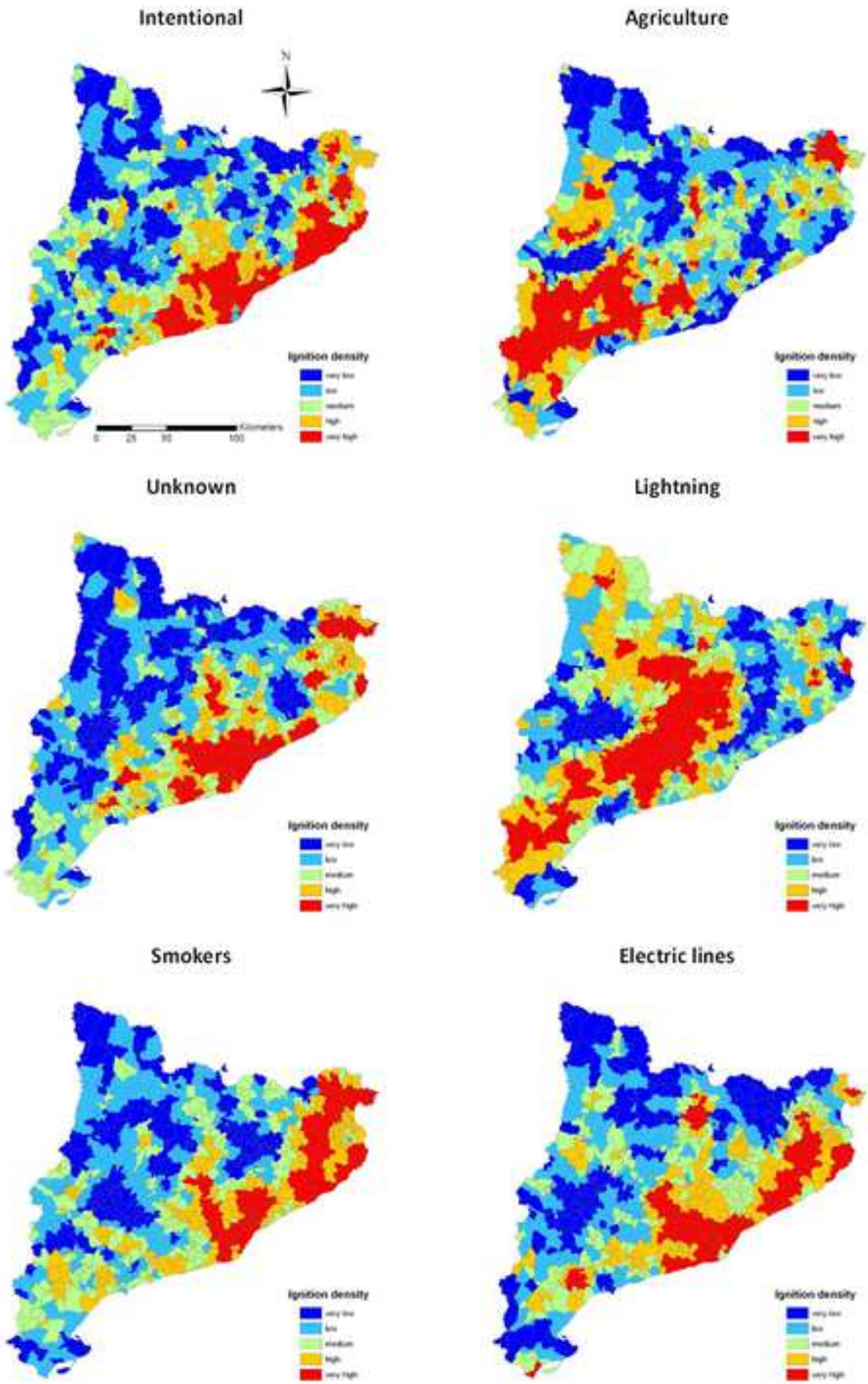

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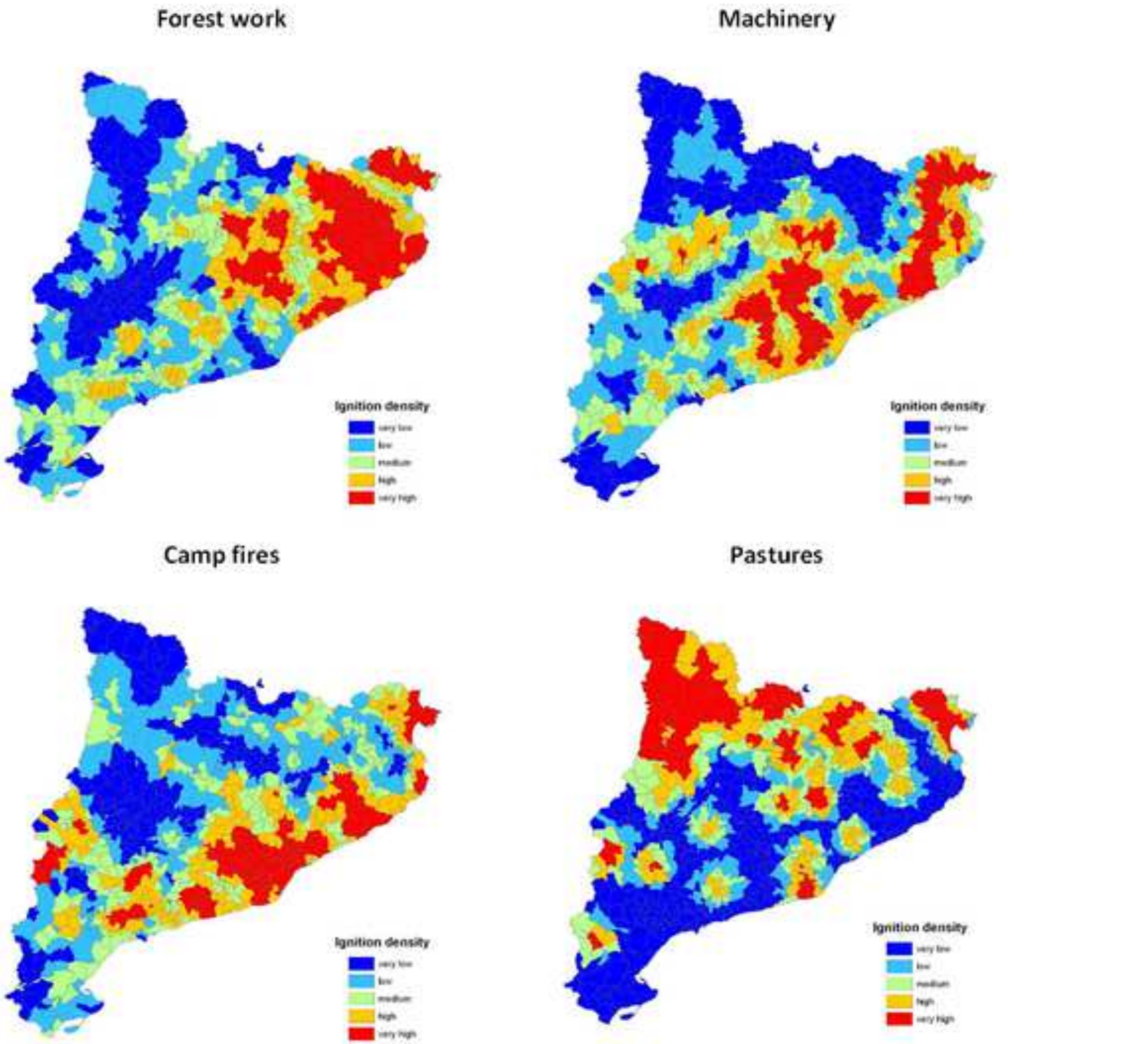

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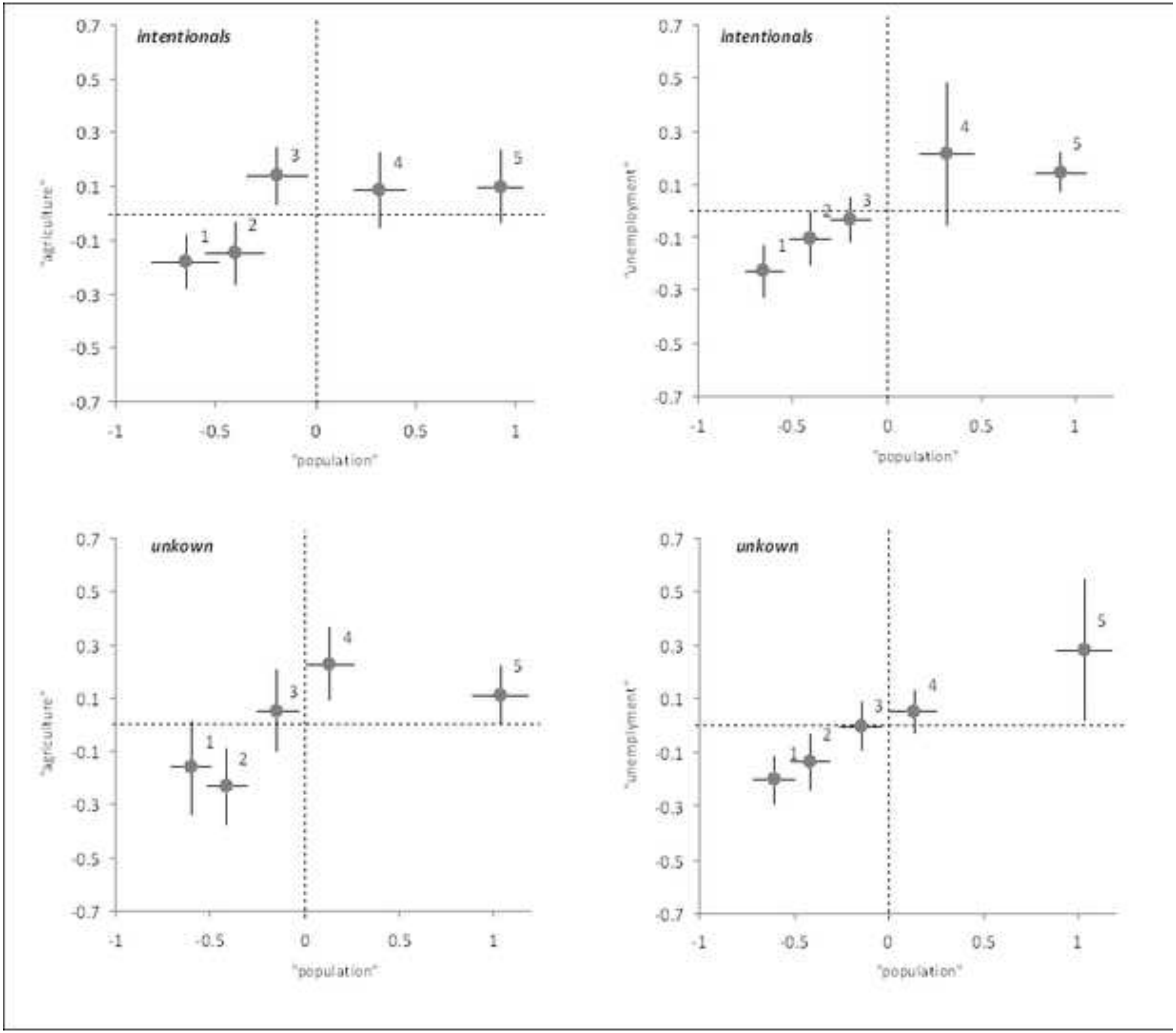

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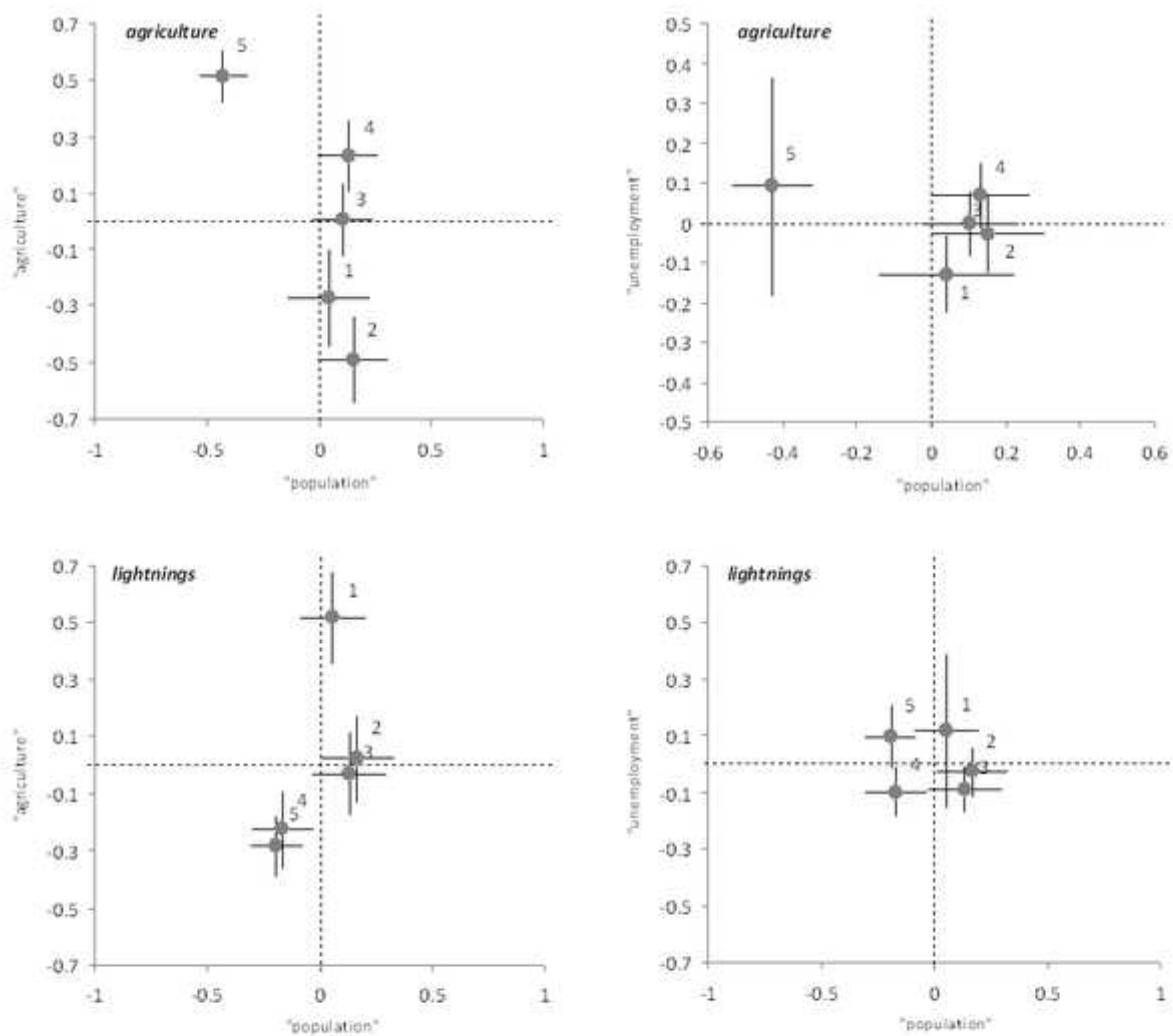

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